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Video Completion in the Presence of Moving Subjects based on Segmentation using Neutrosophic Sets

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Abstract

Image and video completion are essential tasks in the field of image and video processing, often used for restoring damaged regions in images and video frames. The primary challenge in these tasks is to complete them in such a way that they do not introduce noticeable artifacts or inconsistencies to the viewer. While image completion focuses on filling in missing parts in a static context, video completion requires additional considerations due to the temporal dimension. The motion of objects and the preservation of temporal consistency are critical factors in video completion. This research proposes a novel method for image and video completion based on Neutrosophic theory, which handles uncertainty in both spatial and intensity domains. Neutrosophy is utilized to interpret the indeterminacy present in images, allowing for more accurate segmentation and better handling of incomplete data. The proposed method first segments the image using Neutrosophic-based segmentation and then uses the segmented information to guide the completion of missing regions. For video completion, a two-step approach is introduced that separates static backgrounds from moving objects. The background is reconstructed using image completion based on Neutrosophic-based segmentation, and the foreground is completed by identifying appropriate data that best match the missing parts; this data is chosen using a contour-based method, which this method applies neutrosophic sets to get to the most suitable data. The novelty of the approach lies in several key contributions: 1) the use of Neutrosophic theory to handle spatial and intensity uncertainties, 2) a Neutrosophic-based similarity measure for image segmentation, 3) a new metric for finding the most suitable patch for hole-filling, and 4) a novel method for preserving boundaries and uniformity in video completion, particularly in the presence of moving objects. Experimental results demonstrate the effectiveness of the proposed methods, with improved visual quality and reduced inconsistencies compared to previous state-of-the-art methods. However, challenges remain in applying the method to highly detailed images with many classes and handling dynamic backgrounds.

Keywords: Video completion, Video inpainting, Segmentation hole filling, Neutrosophic sets.

1 | Introduction

With the growing role of video content in daily life and advancements in computer-based information retrieval, processing large volumes of videos manually is not feasible. Image and video processing has become a key technique used in various fields like medical imaging, remote sensing, security surveillance, and

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entertainment. One key area of interest in image and video processing is image/video inpainting or restoration, which aims to fill in missing or damaged parts of images and video frames.

Video inpainting, compared to image inpainting, involves both spatial and temporal continuity, making it a challenging task as it requires consistency in motion between frames. Traditional methods for inpainting use texture filling from known parts of the image or video, but they often fail to maintain the correct motion or structure, particularly in videos involving dynamic objects. Common challenges include handling large missing regions, preserving edges, and ensuring temporal coherence.

Despite advances in deep learning and other techniques, challenges such as mismatched frames or loss of object continuity still exist, especially when trying to remove unwanted objects or restore damaged video. Effective video inpainting must, therefore, prioritize selecting accurate information to fill missing regions while maintaining motion consistency across frames.

This research focuses on addressing these challenges, specifically in scenarios involving moving objects in videos with static backgrounds. The objective is to propose a method that improves the selection of data for inpainting, particularly in handling large missing areas, preserving object boundaries, and ensuring temporal coherence, using techniques based on neutrosophic logic.

2 | Related Works

In this section, we will review the studies conducted in various areas related to image and video inpainting. Video inpainting methods can generally be categorized from two main viewpoints [1]: inpainting size at each stage and inpainting method at each stage. Each of these viewpoints will be discussed in detail.

2.1 | Video Inpainting Methods from the Perspective of Inpainting Size at Each Stage

From the perspective of the inpainting size at each stage, there are two broad methods for video inpainting: Patch-based and object-based.

I. Patch-based inpainting methods

These methods are essentially extensions of image-based patch inpainting techniques to video. Several algorithms exist for video inpainting based on patching. While these algorithms perform well when applied to still images, they face challenges when directly applied to videos due to the need to preserve both spatial and temporal coherence. Consequently, modifications to these methods are necessary [2].

II. Object-based inpainting methods

Object-based methods maintain both temporal and spatial consistency simultaneously, producing high-quality visual results.

2.2 | Video Inpainting Methods from the Perspective of Inpainting Methods at Each Stage

When categorizing video inpainting methods based on the method used to fill the missing region, we can identify eight major techniques.

III. Sample-based inpainting: sample-based inpainting algorithms follow these main steps.

- *The target region is initially specified by the user.*
- *The priority of the target region is computed.*
- *A search is conducted to find a matching patch from another frame to fill the target region.*
- *Information is updated in subsequent iterations, refining the inpainting.*

I. Partial Differential Equations (PDE) based Inpainting: These methods work by gradually expanding the known information from the boundary of the missing region inward, using PDE. While these methods perform well when the missing region is small and the target region has texture, they tend to be slow for large holes and may result in blurry outputs [3].

II. Texture Synthesis-based Inpainting: these methods work well for small regions but fail to handle natural scenes effectively and are computationally expensive.

III. Semi-automatic and fast inpainting: these methods require some user input and typically operate in two steps: in the first step, the missing region is initialized by specifying the boundaries, and in the second step, texture synthesis-based patching is used to extend the texture into the missing area [4].

IV. Hierarchical super-resolution inpainting: this method combines sample-based inpainting with image super-resolution techniques.

V. Contour-based inpainting: Ghanbari Talouki and Majdi [5] proposed a contour-based method where, after separating the background and foreground, the background is filled by copying information from neighboring frames where the area is intact. For inpainting moving objects, a similarity measure based on contours is used to match the foreground with other frames to recover the missing content.

VI. Hybrid inpainting

Image segmentation is one of the most challenging tasks in image processing and pattern recognition, playing a crucial role in applications such as robot vision, object detection, medical imaging, and more. Image segmentation refers to the process of dividing an image into different regions where each region is homogeneous, but adjacent regions are dissimilar [6]. Many emerging applications require precise and efficient segmentation mechanisms [7].

Fuzzy set theory, introduced by Zadeh [8], addresses uncertainty in databases by using membership degrees within the interval [0,1]. However, fuzzy sets cannot independently represent the degree of indeterminacy. To resolve this, Smarandache [9] proposed neutrosophic logic and set a broader family of mathematical theories. Neutrosophic sets incorporate three independent membership functions: truth, indeterminacy, and falsity, each represented by a degree in the interval [0,1]. These functions are independent, allowing the representation of uncertainty without mutual dependence.

2.3 | Fuzzy Sets

Fuzzy sets were introduced by Lotfi Zadeh in 1965 to handle imprecise membership in sets. Consider U is the universal set, a subset A in U, in which each element $u \epsilon U$ has a membership function f_A: $U \rightarrow [0,1]$. $f(u) \in [0,1]$ represents the degree of membership of element u in the set A. A membership value close to 1 indicates a high degree of membership, whereas a value near 0 suggests a low degree of membership. Fuzzy sets have been widely used in image processing [10].

2.4 | Intuitionistic Fuzzy Sets

An intuitionistic fuzzy set is a generalization of fuzzy sets, where each element u in U is associated with both a degree of membership $\mu_A(u)$ and a degree of non-membership $v_A(u)$. These values are constrained such that $\pi_A(u) = 1 - \mu_A(u) - v_A(u)$ is the degree of hesitation or doubt of u in set A [11].

2.5 | Neutrosophic Sets

Neutrosophic sets, introduced by Smarandache [9], extend fuzzy sets by considering indeterminacy alongside truth and falsity. A neutrosophic set A in universe U is defined by three functions: truth T_A, indeterminacy I_A, and falsity F_A. These functions are independent and can take values within the extended real numbers range $[-0,1+]$. Unlike fuzzy sets, there are no restrictions on the sum of these three functions, leading to.

$$0 \leq \sup T(u) + \sup IA(u) + \sup FA(u) \leq 3+$$

3 | Proposed Method

At first, video completion methods were generalized from image completion methods based on a space-time perspective. Over time, these methods evolved. The most significant issue that distinguishes image completion from video completion is the temporal continuity of object motion, which must be preserved across video frames. For this reason, directly using image completion algorithms for video completion leads to a loss of video quality. Therefore, modifications need to be made to these methods so they can be applied to video completion.

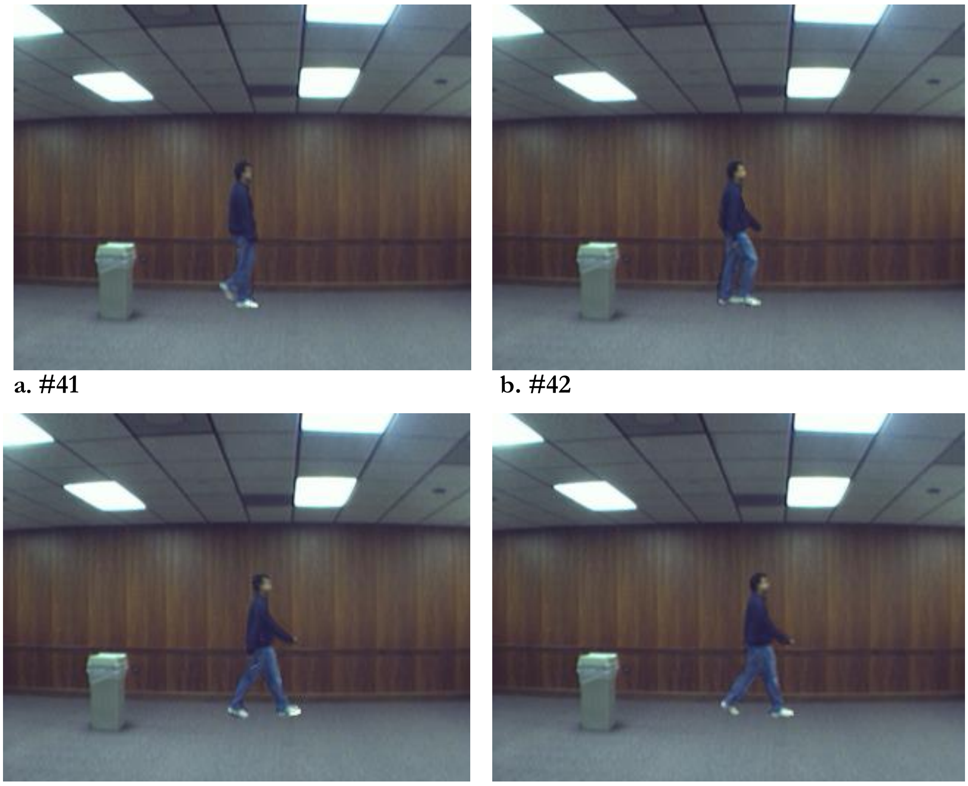
Fig. 1 shows frames from a video completed using the reference method [12]. As seen in *Fig. 1*, in some frames, hands and feet are incorrectly assigned in the completed image. Moreover, in some frames, three hands appear.

In this paper, we aim to remove the occluding object, which is shown in green in *Fig. 2*, and fill the resulting hole using the image completion method based on segmentation in the neutrosophic environment, which was previously introduced and evaluated in [13].

The steps of our video completion method are as follows:

I. Background and foreground (moving object) are separated. This step is explained in Section 3-1.

II. The background in the hole region is completed. If the covering object has a fixed position, no information is available about the region behind it, so we fill the hole in the background using the background painting method based on image completion using segmentation in a neutrosophic environment [13]. If the covering object is not in a fixed position, the information from the region behind it can be obtained from other frames. In this case, we copy the background region from other frames into the whole region.



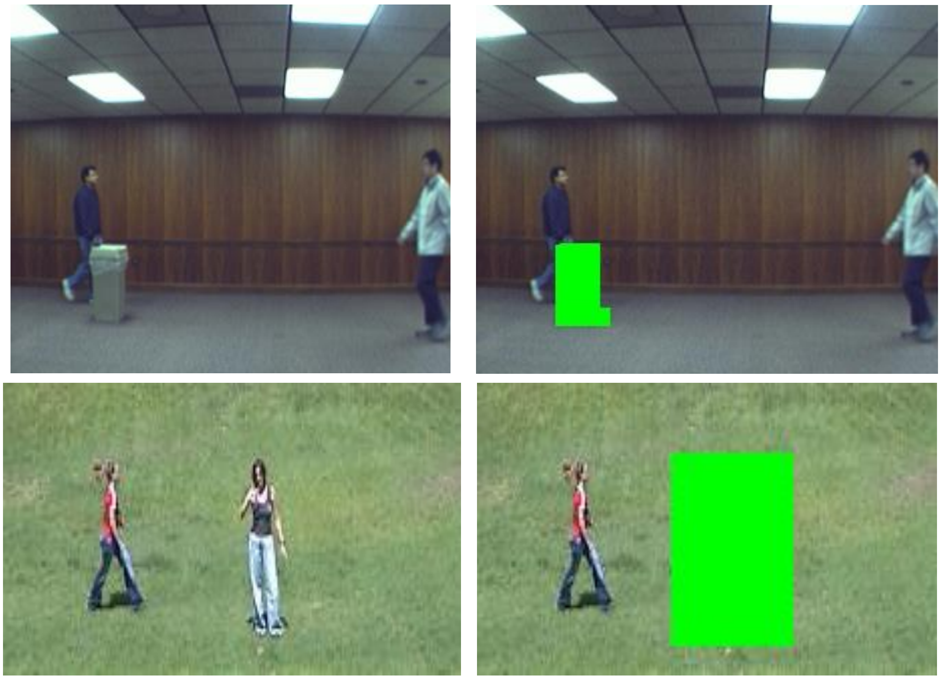
a. #41 **b. #42**

c. #45 **d. #46**

e. #61 f. #62

Fig. 1. Errors in video completion using an object-based method [12].

Frame numbers are listed below each image. (a and b) show a jump in the motion. In (b), two right feet appear. (c and d) show two right hands in frame (c), which is more obvious when compared to frame (d). (e and f) show two right hands in these frames as well.



a. b.

Fig. 2. Mask used for background painting: a. one frame of the video, b. the covering object is removed, and the resulting hole is shown in green.

3.1 | Separation of Moving Objects from the Background

Separation of the foreground (moving object) from the background requires a threshold value, which is applied as *Eq (1)*.

$$FG_t = \begin{Bmatrix} 1 & \text{if } |I_t - BG_{t-1}| > thr \\ 0 & \text{otherwise} \end{Bmatrix}. \tag{1}$$

Where I_t is the frame at time t, BG_{t-1} is the background model, and FG_t is the foreground at time t.

For modeling the background, we use a Gaussian Mixture Model (GMM) [14], where each pixel is modeled as a mixture of k Gaussian distributions. The likelihood of observing a pixel at time t is calculated as *Eq (2)*:

$$P(X_t) = \sum_{i=1}^{k} w_{i,t} N(X_t, \mu_{i,t}, \Sigma_{i,t}). \tag{2}$$

Where $w_{i,t}$ ، $\mu_{i,t}$ and $\sum_{i,t}$ are the weight, mean, and covariance matrix of the ith Gaussian distribution at time t.

Once each pixel is modeled, we approximate the background using the largest B components of the GMM, which is determined by

$$B = \arg\min_{b}\left(\sum_{k=1}^{b} w_k > T\right). \tag{3}$$

Where T is the smallest information threshold considered as background. After applying this method, moving objects are detected by subtracting the background from each frame.

After this separation, additional noise may appear in other regions of the frame. To remove this noise, regions are labeled, and their areas are calculated. Only those regions with larger areas than others are retained, and the remaining noise is removed by zeroing out the corresponding pixels. This process results in a noise-free background-foreground separation. *Fig. 4* shows the separation of the moving person from the background in the presence of noise, while *Fig. 5* shows the separation after noise removal.

Fig. 4. Separation of a moving person from the background in the presence of noise.

Fig. 5. Separation of a moving person from the background after noise removal.

3.2 | Background Inpainting

The videos used in this paper are of the static background with a moving person type. Therefore, to restore the background, we use the image completion method based on segmentation in a neutrosophic environment, which was introduced in [13]. As shown in *Fig. 6*, the covering object has a fixed location, so we can paint one frame and copy the position of the occluding object to other frames. *Fig. 7* shows the result of filling the background for the hole in *Fig. 2b.*

3.3 | Qualitative Comparison of Video Completion Results

Fig. 8 compares frames from the results obtained using the proposed method with those obtained using the method from [15].

3.4 | Quantitative Comparison of Video Completion Results

To quantitatively compare the results of video completion, the ASVS criterion is calculated for all frames, and its average value is determined. A smaller ASVS value indicates better completion of the target region. *Table 1* shows the ASVS values for our results and the results from the method [15].

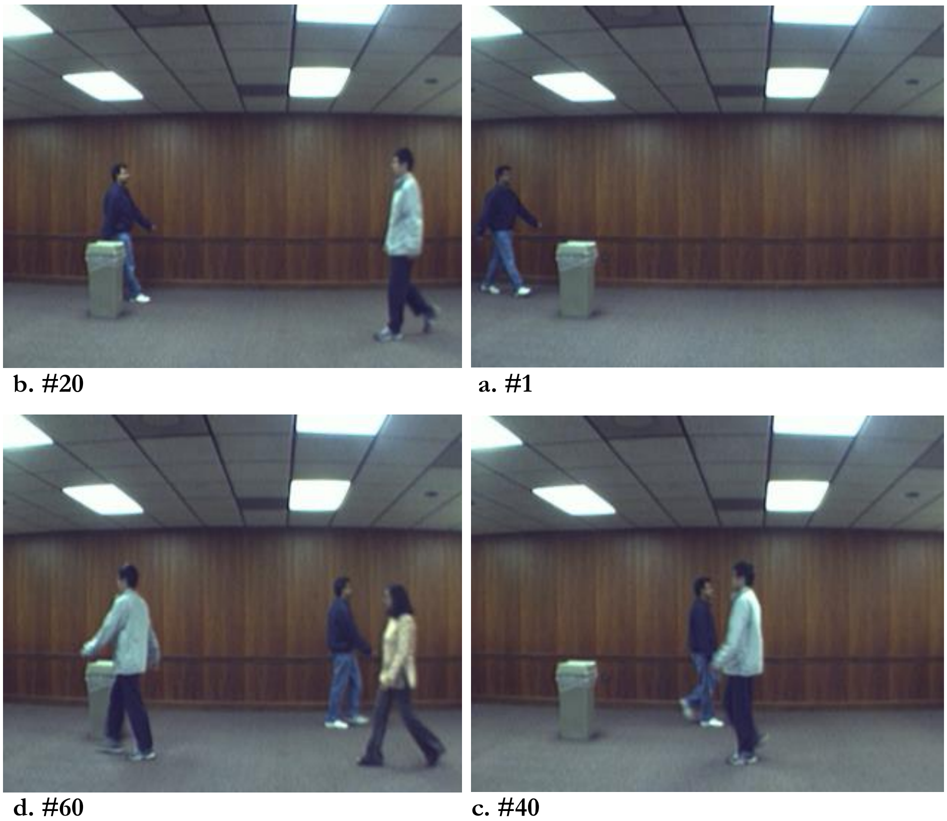
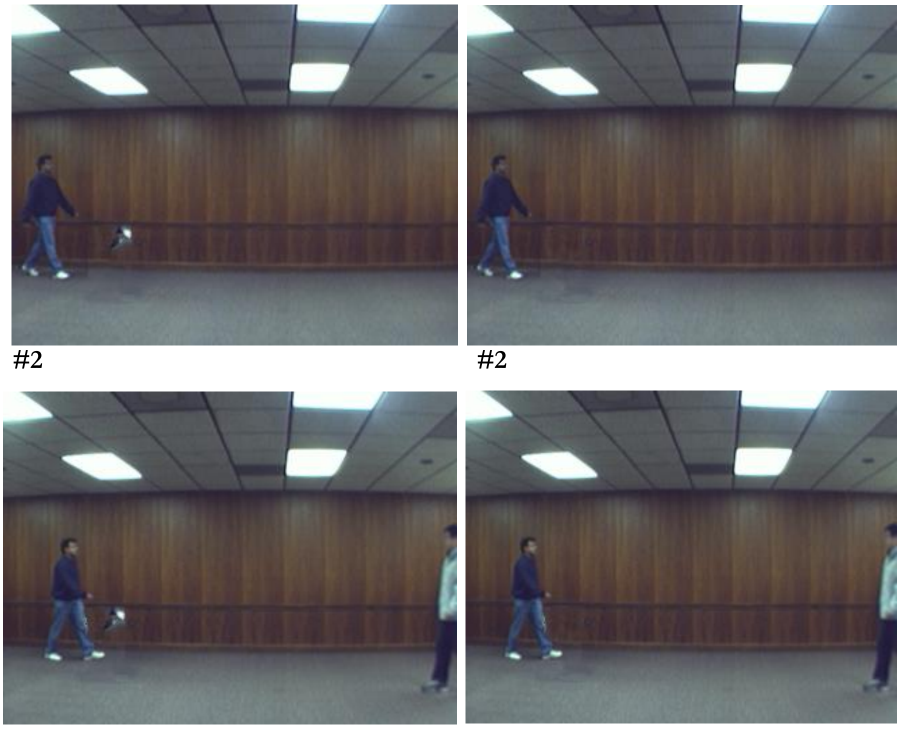


Fig 6. Static covering object. Frame numbers are written below the image.

Fig 7. Background completion result.



#2 #2

a. #10 b. #10

Fig 8. Comparison of video completion by the method presented in this treatise and the method [15] (column); a. Video frames completed by [15] method, b. Video frames completed by segmentation-based image completion method in the Neutrospheric environment.

Table 1. Comparison of results from the proposed method with those from [15] based on the ASVS criterion.

Zhang et al. [15]	0.1374
Proposed method	0.0961

4 | Conclusion

Image and video completion play a significant role in image and video processing, especially for repairing damaged regions in images and video frames. The primary goal of image completion is to fill in damaged areas in such a way that no perceptible inconsistency is introduced to the viewer. Video completion is more complex since it requires maintaining temporal consistency, meaning that when completing a video with moving objects, the completed regions must blend seamlessly, and the motion of the moving objects must be preserved.

4.1 | Innovations

The innovations of this research include:

I. Considering spatial and intensity ambiguities with the Neutrosophic concept.

II. Proposing a similarity measure to find the most appropriate patch for hole completion.

III. Neutrosophic-based image completion using segmentation.

IV. Completing video with moving objects based on Neutrosophic segmentation, preserving boundaries and uniformity while reducing fragmentation.

4.2 | Suggestions

Based on the results of the video completion method introduced in this thesis, the following problems and suggestions are proposed for future research.

I. The videos used in this research have static backgrounds. Dynamic backgrounds were not considered.

II. The motion of the camera and size variations of the moving object throughout the video were not addressed.

III. The case where no healthy sample of a moving object can be found in other frames was not considered. In such cases, the motion of the moving object should be reconstructed.

Author Contributions

Amanna Ghanbari Talouki conceptualized the study, developed the Neutrosophic-based segmentation and video completion methods, and conducted experiments. Abbas Koochari contributed to the video completion technique and assisted in data analysis. Seyyed Ahmad Edalatpanah provided support with algorithm development and contributed to manuscript revision.

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Data Availability

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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